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A Framework to Implement Probabilistic Fatigue Design of Safe-Life Components

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ABSTRACT

Safety-critical components, such as aircraft landing gear, are designed using the 'safe-life' fatigue analysis process. Variability exists within materials data, loads data and component dimensions and is currently mitigated using safety factors. Probabilistic approaches to safe-life fatigue design have been proposed to better represent this variability. However, challenges currently exist that prevent the wider utilisation of a probabilistic approach. This paper presents a framework that aims to overcome these challenges. The statistical characterisation, probabilistic, surrogate modelling and sensitivity analysis methods required to implement the framework are introduced. Finally, a discussion of how recent advances within aerospace fatigue design, such as 'big-data', can be used to support a probabilistic framework is presented.

Keywords: *Safe-life, Fatigue Design, Probabilistic Methods, Surrogate Modelling, Big-Data.*

INTRODUCTION

Within the aerospace sector, aircraft landing gear are classified as 'safe-life' components (Braga, 2014). The 'safe-life' of a component represents the life (often defined in flight-hours or flight-cycles) at which the component must be retired from service. Component safe-life values are computed using 'classical' fatigue analysis methods, such as a stress-life (S-N) approach incorporating Miner's Rule (Braga, 2014). However, safe-life fatigue analysis contains many sources of variability within the design parameters of the analysis process, such as scatter in material properties and uncertainty in loading (Hoole, 2018). This variability propagates through the analysis process into component safe-life values and is currently accounted for using

conservatism and safety factors (Hoole, 2018). The use of safety factors is known as a ‘deterministic’ approach, whereby all design parameters are set to single and safe values. The introduction of conservatism into the analysis process could lead to components being ‘over-sized’, increasing component weight and life-cycle cost, thereby compromising the performance of the overall structure (Suresh, 1998). In addition, conservatism can also lead to the potential component safe-life not being fully exploited due to early retirement from service.

Probabilistic approaches to fatigue design and analysis enable the variability in design parameters to be statistically characterised using probability distributions (e.g. Normal, Weibull, etc.) (Ocampo, 2011). The statistical characterisation of design parameters permits the variability to be propagated through the safe-life analysis process to produce an output probability distribution of the accumulated fatigue damage or the component safe-life. The component reliability (or probability of failure) associated with the component safe-life can then be computed from the output probability distribution. The probability of failure can also be computed as the probability of the accumulated fatigue damage (as calculated using Miner’s rule) exceeding the failure criterion value of 1. A probabilistic approach therefore offers the opportunity to better represent and understand the variability within component safe-life values, increasing the confidence in the component retaining its structural integrity throughout its design safe-life. This increased confidence has the potential to yield more efficient designs that remain safe in-service.

However, the development, implementation and adoption of a probabilistic framework requires the accumulation of a wide range of technical knowledge and experience, along with the development of a mindset of accepting variability within design parameters. In addition, there are a significant number of ‘blockers’ and challenges that currently prevent the wide-scale implementation of probabilistic methods within safe-life fatigue design (Goh, 2009). This paper aims to document the authors’ experience in developing a probabilistic framework to date. This will be achieved through presenting a high-level framework for implementing a probabilistic approach for the fatigue design of safe-life components that can overcome the current challenges. In this context, a framework is defined as the required inputs, methods and interactions with other areas of aerospace design required to successfully implement a probabilistic approach.

JUSTIFICATION FOR DEVELOPING A PROBABILISTIC FRAMEWORK

This section introduces the justification for developing a probabilistic framework to safe-life fatigue design, through considering improved modelling, exploitation of data and challenging of existing conservatism.

Firstly, fatigue as a phenomenon and engineering challenge is inherently probabilistic (Schijve, 2009). Variability in the number of cycles to failure is observed within the datasets used to generate S-N curves (Schijve, 2009). Variability is also present within the in-service loading of aerospace components, including loading magnitude, the

occurrence of specific manoeuvres, along with the sequence of loads and flights. Dimensional variability may also be present within components (Haugen, 1980). Therefore, a probabilistic approach provides the only route to capturing and retaining these sources of variability within the design and analysis process (Haugen, 1980). Probabilistic approaches therefore represent improved modelling of fatigue as a failure mode, potentially increasing confidence in analysis methods and reducing the conservatism required within fatigue design. Through computing a probability of fatigue failure, probabilistic approaches also provide the only route for combining failure modes for a component (Long, 1999). For example, the probability of fatigue failure and probability of tensile overload can be combined to produce a single probability of failure for the component.

The computation of a probability of failure using a probabilistic framework also has an advantage over the deterministic approach based upon safety factors due to its ability to challenge the conservatism required within fatigue design (Long, 1999). Whilst existing safety factors have been shown to provide sufficient conservatism to prevent in-service fatigue failures, it is not possible to quantify ‘how’ conservative existing safety factors are, potentially leading to over-designed or over-weight components. A probabilistic framework enables the conservatism to be quantified using the component probability of failure or reliability (Haugen 1980). This could support a challenge of the conservatism currently required with the aim of increasing component efficiency.

Within safe-life fatigue design and analysis, significant resources are expended during material testing and loading spectra development, resulting in a significant amount of data being available for fatigue design (Schijve, 2009). However, especially in the case of generating material design allowables, this data is used to produce a single safe value to be used for design (Hoole, 2018). As probabilistic approaches utilise the complete dataset to generate input probability distributions, this increases the utilisation of data that is already available for design. In addition, probabilistic approaches provide an opportunity to critically review existing assumptions regarding the statistical characterisation of fatigue design data (Siddall, 1983).

Probabilistic approaches can utilise Sensitivity Analysis (SA) methods which permit the identification of design drivers (Zentuti, 2017). SA methods are a group of techniques which apportion the variability in the output of a process (e.g. variability in component safe-life values) to the variability in specific input design parameters (e.g. materials data, loads data, etc.) (Hoole, 2016). Results from SA can be used to identify design drivers which have the greatest impact on the component safe-life. Future work can then be focused on better characterising or controlling the variability in the design drivers (Hoole, 2016). SA can also be used to challenge the conservatism currently used, as it may highlight areas of the safe-life fatigue analysis process where safety factors are either under or over conservative (Hoole, 2016).

Finally, a probabilistic approach enables the implementation of Reliability-Based Design Optimisation (RBDO). RBDO is an approach that enables design parameters

to be optimised whilst achieving a desired level of reliability and has seen implementation within aerospace fatigue design (d'Ippolito, 2007).

Therefore, it has been shown that a probabilistic framework can increase component efficiency, through improved modelling, increased data utilisation, challenging of conservatism and design optimisation.

REQUIRED METHODS AND FRAMEWORK FOR A PROBABILISTIC APPROACH

This section presents an introduction to the selection of methods required to implement a probabilistic framework for safe-life fatigue design. This section also aims to demonstrate how each of the methods interact with one another in a high-level framework.

Statistical Characterisation of Fatigue Design Data

The first group of methods required are Statistical Characterisation methods. These methods are used to 'fit' and 'select' the probability distribution types to be used to represent the variability in materials (e.g. S-N datasets), loads and dimensional design parameters (Booker, 2001). 'Fitting' is the process of estimating the distribution parameters of a distribution and is performed using probability plotting and maximum likelihood methods (Bury, 1999). These parameter estimates define the Probability Density Function (PDF) of the distribution. 'Selection' of the final distribution type is performed using 'Goodness-of-Fit' (GoF) tests, such as Chi-Squared and Anderson-Darling, in order to accept or reject a candidate distribution (Bury, 1999). As the accuracy of probability of failure values from a probabilistic framework is dependent on the accuracy of the statistical characterisation of design parameters, it is recommended that a robust approach to statistical characterisation is used. This can be achieved using multiple fitting and GoF methods for validation, to ensure the generation of accurate input probability distributions.

Within probabilistic approaches it is vital to represent correlations which may exist between design parameters (i.e. where the value of one design parameter impacts the value of another design parameter), as is common in landing gear loads data (Bauxbaum, 1981). Correlation coefficients such as Pearson, Spearman and Kendall can be used to quantify the correlation between design parameters. In order to generate correlated random samples, Copulas can be constructed to represent the correlation structures that can exist between design parameters (Genest, 2007).

Probabilistic Methods

Following statistical characterisation, the probabilistic method used to propagate the variability through the safe-life fatigue analysis process can be considered. The most basic probabilistic method is a Monte Carlo Simulation (MCS), which essentially evaluates the existing analysis process over many (often millions) of iterations, each time sampling new values from the input probability distributions (Echard, 2014).

This results in a distribution in the output values, enabling a probability of failure to be computed. Whilst an MCS will retain the full complexity of the existing analysis process, the computational expense can be prohibitive, especially when computing the low probability of failure values associated with aerospace design and for quick-iteration early design phases (Echard, 2014).

Therefore, a series of alternative probabilistic methods have been proposed in order to improve on the computational expense of an MCS approach. The first is the Stress-Strength Interference (SSI) approach (Ferlin, 2009). This approach is based upon generating a ‘Stress’ distribution (e.g. the accumulated fatigue damage) and a ‘Strength’ distribution (e.g. the variability in the failure criterion for Miner’s Rule). The overlap between these two distributions is proportional to the probability of failure as shown in Figure 1a. Figure 1b demonstrates how the probability of failure is computed when a deterministic design criterion is used. However, the SSI approach often requires assumptions to be made about the Stress and Strength distribution type and may even require an MCS to be performed to generate the distributions, failing to negate the computational expense of an MCS approach (Echard, 2014).

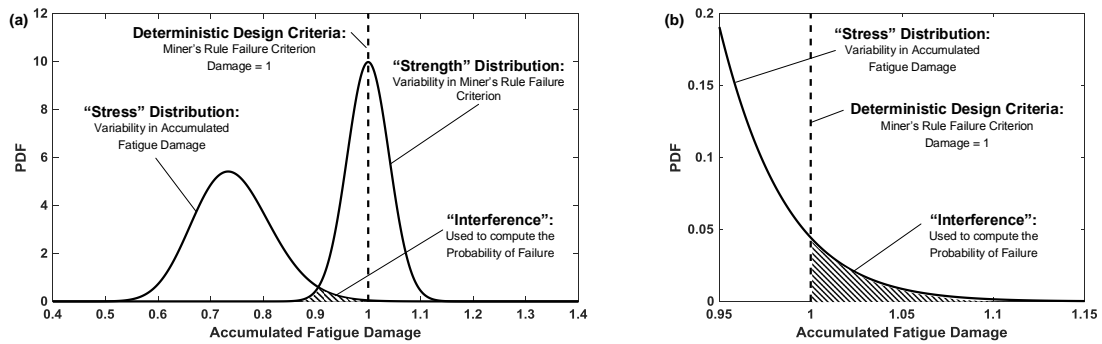


Figure 1: (a) A visualisation of the Stress-Strength Interference Approach and (b) Probability of Failure Computation for a deterministic design criterion.

An extension of the SSI approach are the Limit State Approximations (LSAs) such as the First Order Reliability Method (FORM) (Goh, 2009). LSAs convert the SSI approach into a normalised space and identify a ‘most probable point’ (i.e. the combination of parameter values that maximises the probability of failure) (Echard, 2014). The probability of failure can then be computed using closed-form equations. Whilst LSAs are widely applied, they are not suitable for applications with non-Normal input distributions or highly non-linear processes (Goh, 2009).

Other approaches have focused on speeding up MCS directly, through modifying the sampling strategy used. Latin Hypercube Sampling (LHS) is a stratified sampling approach, which divides each input probability distribution into a series of bins which have an equal probability of being sampled from (Zentuti, 2017). Each bin is sampled from once. LHS ensures that there is a sample within each bin, whilst MCS can result in multiple samples in some bins and no samples in others (Zentuti, 2017). LHS can therefore reduce the number of process evaluations required, as LHS ensures that all parts of the input distribution are sampled from (Zentuti, 2017).

Surrogate Modelling

Within the safe-life fatigue analysis process, Finite Element Analysis (FEA) methods are often employed to compute internal loads and stresses within components. As fatigue analysis requires stress analysis to be performed for many individual cyclic loads, the computational expense of running a full FEA within a probabilistic approach can be significant, if not prohibitive. Also, probabilistic approaches may require key elements of the FEA model to vary, such as component dimensions and material stiffness as sampled from the input probability distributions. This can increase the computational expense further and probabilistic frameworks often require significantly more FEA evaluations than the existing fatigue analysis process.

Surrogate Modelling (SM) methods can be used to reduce the expense of computationally-intensive elements of the safe-life fatigue analysis process. The purpose of SM methods is to replace the computationally expensive element (known as a ‘model’) with an alternative surrogate model that requires less computational resource to evaluate, whilst still accurately representing the relationship between the input and the output of the original model (Echard, 2014). SM methods require ‘training’ data which is used to train the surrogate model and ‘validation’ data which is used to test the accuracy of the surrogate model output when provided with new and ‘unseen’ input values (Holmes, 2016). Training and validation data is produced by performing evaluations of the original model, whereby the input parameters are varied for each evaluation using full-factorial design or LHS (Holmes, 2016).

The simplest SM method is known as the Response Surface Method (RSM). RSM is a polynomial surface across N dimensions, where N is the number of input parameters to the model (SAE, 1997). The polynomial equation (typically either quadratic or cubic) defining the RSM is fitted to the training data using least squares regression (SAE, 1997). The advantage of RSM it is quick to train (typically < milliseconds) and intuitive to use, due to its similarity to ‘curve’ fitting of data (Simpson, 2001). The limitation of RSM however is that it cannot be applied to models with significant non-linearity or high dimensionality (Forrester, 2009).

To improve the ability of surrogate models to represent models with high dimensionality or high non-linearity, non-parametric regression methods have been developed which do not rely on an existing polynomial surface shape. Non-parametric methods construct a surrogate model by combining a series of ‘basis’ functions with assigned weights to produce a smooth-fit to the training data (Holmes, 2016). Such methods include Radial Basis Functions (RBFs) (Simpson, 2001) and Gaussian Process Regression (GPR) (Holmes, 2016). GPR and RBF typically require larger training datasets and longer training times (typically minutes).

The final class of SM methods are machine-learning methods, such as Artificial Neural Networks (ANN). ANN replicate the behaviour of the human brain in order to learn the relationship between the training data outputs and training data inputs (Cross, 2012). The ANN architecture is made up of a series of layers of ‘neurons’ which are comprised of a transfer function (usually sigmoid) along with weights

(Cross, 2012). The ANN is trained using sophisticated optimisation processes by adjusting the weights for each neuron in order to minimise the error between training data output values and the output values of the ANN (Cross, 2012). ANN methods are suitable for high dimensional models, along with highly non-linear models (Simpson, 2001). The limitation of an ANN approach is increased time and experience required to define the ANN architecture (e.g. number of neurons) and the training time required to produce the neuron weights (typically hours) (Simpson, 2001).

Sensitivity Analysis

This section focuses on the methods available for performing SA, along with additional applications of the results from SA. Further detail on each of the SA methods introduced within this section is available in Zentuti et al (Zentuti, 2017).

Probabilistic Variance-Based Sensitivity Analysis (VBSA) methods have been developed in order to apportion the variance (the statistical measure of variability) in the process output (e.g. safe-life) to the variance in the input probability distributions (Zentuti, 2017). The finite difference variance equation approach provides a method based upon the derivative of the process output with respect to a change in each input parameter and the variance of each input parameter (Booker, 2001). Sobol indices are an alternative measure of how the variance in the process output changes when each input parameter is fixed to a single value one-at-a-time (Hoole, 2016). Sobol indices have been previously applied to the safe-life fatigue analysis of landing gear components (Hoole, 2016). The limitation of VBSA methods is that as they only assess variance, VBSA methods may not produce accurate results when the input and output distributions are highly-skewed (i.e. non-Normal) (Zentuti, 2017). This is of particular concern in fatigue analysis where S-N datasets are typically characterised using Log-Normal and Weibull distributions and loads data is often characterised using an Exponential distribution.

Global Sensitivity Analysis (GSA) methods focus on quantifying how the probability distribution shape of the process output varies as the input parameters are fixed to a single value (Zentuti, 2017). This enables the sensitivity of highly-skewed output distributions to be apportioned to highly-skewed input distributions (Zentuti, 2017).

SA methods can also be used to identify input parameters that are not influential on the output of a model in a process known as ‘screening’ (Pianosi, 2016). For example, if a specific component dimension was found not to significantly change the stress within an FEA model, it could be kept as a constant within the surrogate model, potentially reducing the amount of training data, training time and surrogate model complexity required (Pianosi, 2016). Likewise, within the probabilistic methods, non-influential parameters can be modelled as deterministic values, rather than using probability distributions (Pianosi, 2016). This reduces the number input parameters to be sampled, potentially reducing the computational expense of the probabilistic method. Therefore, SA methods also ‘feedback’ into the SM and probabilistic methods.

Framework for Probabilistic Approach to Safe-Life Fatigue Design

As the previous sections have shown, there are a wide range of methods required to implement a probabilistic approach. Figure 2 shows a high-level framework of a probabilistic approach that visualises the many interactions that exist between each of the methods described in this section. Figure 2 also highlights how the probabilistic methods interact with the existing safe-life fatigue analysis process.

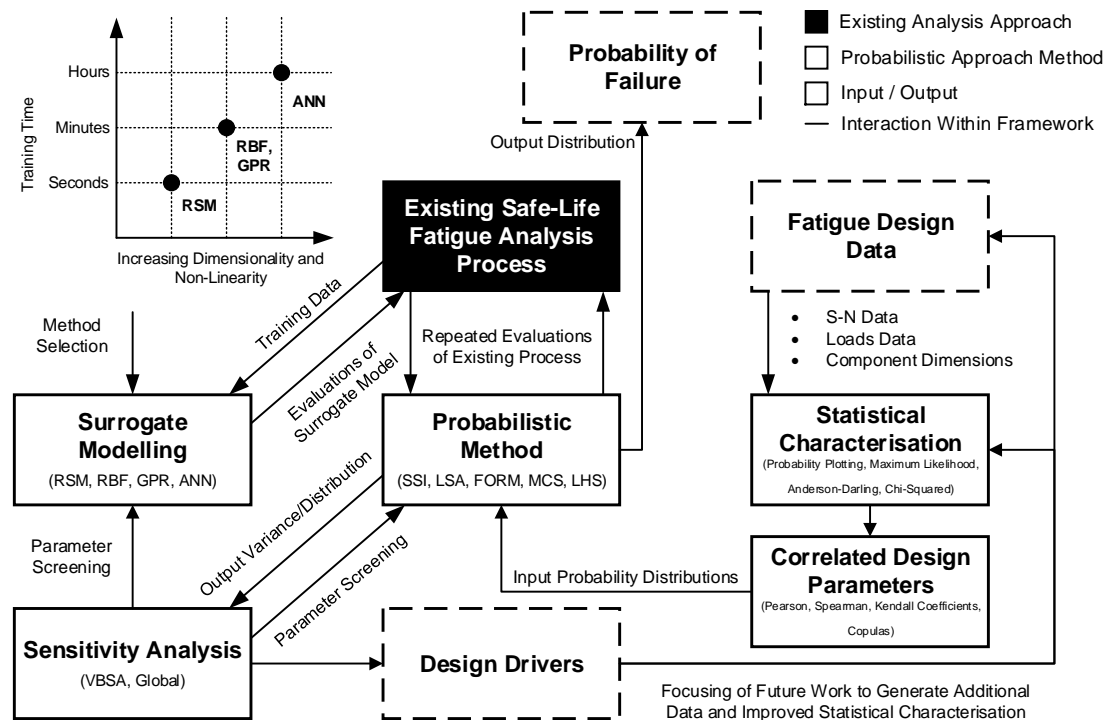


Figure 2: A framework for the implementation of a probabilistic approach to the fatigue design of safe-life components, including the interaction between the required methods.

Figure 2 demonstrates how all of the methods required for the probabilistic framework treat the existing safe-life fatigue analysis process as a ‘black-box’. Therefore, the probabilistic framework is superimposed onto the existing analysis process, rather than intending to replace the existing process. As a result, the accuracy of results from a probabilistic framework are highly dependent on the accuracy of the existing analysis process, including existing physics-of-failure models (e.g. Miner’s rule for fatigue crack initiation). Consequently, the development of a probabilistic framework provides a suitable opportunity to assess, review and challenge the uncertainty and assumptions present within the existing analysis process. Finally, as all of the methods within the framework interact with the existing fatigue analysis process, the characteristics of the existing process (e.g. non-linearity, dimensionality, etc.) will also impact the selection of the methods to utilise within the framework.

PREVIOUS PROBABILISTIC APPROACHES TO SAFE-LIFE FATIGUE DESIGN

Within the literature, probabilistic approaches for safe-life fatigue design have been previously developed for light aircraft structures (Ocampo, 2011) and elements of rotorcraft structures (Zhao, 2010) (Dekker, 2016). The work of Ocampo et al developed a comprehensive probabilistic approach to assess the probability of failure for the continuing operation of safe-life light aircraft structures based upon an MCS probabilistic method (Ocampo, 2011). Cortina et al also demonstrated the application of SA methods based upon the probabilistic approach proposed by Ocampo et al (Cortina, 2012). Within the rotorcraft sector, LSA approaches have been previously applied by Zhao and Adams (Zhao, 2010) and an MCS-based approach has been proposed by Dekker et al (Dekker, 2016).

Current research work by the authors aims to develop a probabilistic approach for the fatigue design of safe-life aircraft landing gear components. Whilst probabilistic methods for fatigue design are yet to be applied to safe-life landing gear components, this work further aims to develop additional tools to support the wider implementation of probabilistic methods, along with exploiting recent advances within the aerospace sector. These tools and advances will be discussed as means to counteract the challenges currently facing the implementation of probabilistic approaches in the remainder of the paper.

CHALLENGES OF IMPLEMENTING PROBABILISTIC APPROACHES

A series of challenges currently exist regarding the implementation of probabilistic approaches and these act as ‘blockers’ to the further application of such approaches, not just to safe-life fatigue design but also to the wider engineering community. This section will discuss each of the areas of challenge and demonstrate how recent advances in aerospace fatigue design can be employed to overcome these challenges. The content of this section presents on-going work being conducted by the authors.

Computational Expense

One of the most significant challenges regarding probabilistic approaches is their increased computational expense when compared to existing design processes (Goh, 2009). This is especially the case at early design phases where iterations and design changes are often required to be rapid, but also during mature/certification level design phases where complex analysis processes are often already computationally expensive. In order to reduce computational expense, SM and screening from SA must be utilised within a probabilistic framework.

Selection of Methods

Within the probabilistic approach there are often many specific methods that can be selected. However, it has been observed by the authors that there is often little practical guidance available for new practitioners to assist in the selection of the most

appropriate methods for a given design task (Goh, 2009). The selection of methods is a complex interaction between the:

- **Intended Application:** How accurate, fast and robust must the probabilistic approach be?
- **The Characteristics of the Existing Process:** Is the existing process highly dimensional, highly non-linear and does it contain any computationally expensive models?
- **The Characteristics of the Input Probability Distributions:** Are datasets characterised by Normal or skewed distributions? Do correlations exist between design parameters?
- **The Strengths and Limitations of each Method**

Current work by the authors aims to consolidate the available literature into a series of pro-forma and trade-off study tables to assist new practitioners in selecting the most appropriate methods for their specific application, including considerations regarding design stage maturity.

Verification and Validation

The failure to successfully implement probabilistic frameworks is often as a result of lack-of-confidence in the required methods and the accuracy of results. Confidence in a probabilistic framework can be achieved through verification and validation. ‘Verification’ is defined as ensuring that the computer program of the framework (i.e. the programs used to implement the statistical characterisation, probabilistic methods, surrogate models, etc.) are operating correctly (Goh, 2009). This can be achieved through rigorous testing of the computer programs used. ‘Validation’ is defined as comparison of output results with existing data or results generated using alternative methods. For example, the surrogate models constructed can be validated using the ‘unseen’ validation data. In addition, the probability distributions generated within statistical characterisation using maximum likelihood methods can be validated using probability plotting methods.

The challenge of validating a probabilistic framework lies within the validation of the computed probability of failure. Within the aerospace sector, where only limited full-scale testing is economically viable, experimental data is unlikely to be available to validate the computed probability of failure (Long, 1999). Therefore, validation can only be performed through comparison with an alternative probabilistic method. For example, an SSI, LSA or LHS approach could be validated using an MCS approach. An MCS provides a suitable validation benchmark as it is simply repeated evaluations of the existing analysis process. However, the computational expense of conducting an MCS for validation could be prohibitive. This could be alleviated with the use of verified and validated surrogate models, or through the utilisation of High-Performance Computing (HPC). HPC is informally known as ‘supercomputing’ and uses multiple computer clusters and parallel processing in a ‘brute force’ approach to reduce the computation time for an MCS.

Availability of Data

One of the common challenges towards developing a probabilistic approach is that the required data is either not available or would be too costly to generate. Recent advances within the aerospace fatigue design sector regarding ‘big-data’ are enabling the generation and capture of data that can support a probabilistic approach to safe-life fatigue design. ‘Big-data’ is defined as datasets that are large in size and are often generated autonomously (Graham, 2017). An example of ‘big-data’ relevant to the probabilistic safe-life design of landing gear components is the online tracking of flights using services such as FlightRadar24 (FlightRadar24, 2018), which can provide operational statistics to support studies into the variability in aircraft operations. Likewise, as ‘real-time’ data streaming of aircraft loads continues to mature (Graham, 2017), the incorporation of actual aircraft loads into probabilistic fatigue design becomes more of a possibility. These advances improve the accuracy of the results from a probabilistic framework through richer datasets that can be used to improve the characterisation of input probability distributions.

Mindset Change and Design Criteria

Another challenge within the aerospace sector is the need to develop probabilistic design criteria which are equivalent to the Miner failure criterion of 1 currently used within safe-life fatigue design. Within a probabilistic approach, design criteria take the form of an acceptable probability of failure or ‘target reliability’ (Long, 1999). In many cases such values will not be currently available. However, the following approaches are proposed to generate target reliability values:

- Based upon the intended reliability derived from existing safety factors. For example, the resulting reliability based upon the scatter observed in the full-scale testing of ‘built-up’ components (Habermann, 2007).
- Based on certification guidelines, such as demonstrating that a component failure that could result in a catastrophic event such as the loss of an aircraft achieves the CS25 requirement of occurrences no greater than 10^{-9} per flight hour (EASA, 2016). Such an approach has been previously demonstrated in the ‘six nines’ reliability target for military helicopters (Zhao, 2010).
- Based on current in-service failure rates (if acceptable) (Schmidt, 2017).
- As part of the safety and reliability ‘budget’ from Failure Mode, Effects and Criticality Analysis (FMECA) (Booker, 2001).

Long et al provide an excellent discussion on the potential legal, technical, regulatory and socio-economic impacts of developing target reliabilities within the aerospace sector, due to the need to accept that a component will have a finite probability of failure (Long, 1999). This mindset change represents one of the most significant challenges when transitioning to a probabilistic approach.

Technical Knowledge and Resources Required

The final challenge regarding the adoption and implementation of a probabilistic approach for the safe-life fatigue design of aerospace components is the significant technical knowledge that is required to construct such an approach. There is a wide range of often complex methods that are required to be understood, verified, validated and implemented. Naturally, this represents a high resource burden on engineers and practitioners wishing to implement such methods. Therefore, in order to achieve further benefits from the expenditure of the resources required to implement a probabilistic approach, it is useful to highlight other areas within which the methods required for a probabilistic approach can be utilised.

Firstly, the wider use of ‘big-data’ within aerospace fatigue design will require the robust, systematic and rapid statistical characterisation of data. Therefore, the statistical characterisation methodologies implemented for the probabilistic approach could also be used to characterise the datasets from the anticipated increase in ‘real-time’ reporting of aircraft loads in-service.

The use of optimisation methods within design are widespread across the aerospace sector and have recently been applied to the design of landing gear assemblies (van Ginneken, 2016). As optimisation approaches (especially RBDO) often require repeated evaluations of computationally expensive FEA models, the SM methods used within a probabilistic approach could also be used to support optimisation-based design. For example, the FEA model of the landing gear structure could be replaced with an RSM, such that the optimisation process is conducted using the surrogate model, reducing the computational expense. This reduction in computational expense could also permit a greater number of optimisation iterations to be performed. In addition, a working understanding of optimisation methods is required to successfully implement the maximum likelihood statistical characterisation methods and the methods used to train the surrogate models (Bury, 1999). Therefore, it can be seen that a probabilistic approach and optimisation approach to safe-life fatigue design are closely linked and reliant on the methods used within each approach.

Finally, combining the need for rapid-evaluations of computationally expensive models and the development of big-data is the recent utilisation of ‘digital twins’ within aerospace fatigue assessment and in-service monitoring of components (Graham, 2017). Within a digital twin, a mathematical model of an in-service component is updated based upon in-service data in real-time (e.g. monitoring the fatigue damage accumulation in a component) (Graham, 2017). The SM methods described within this paper could therefore also be employed within a digital twin approach, with a view to reducing the computational expense of performing ‘real-time’ fatigue assessment and monitoring of in-service components.

Therefore, this section has shown that there are significant opportunities for the technical knowledge and methods required for a probabilistic approach to be utilised and exploited within other aspects of aerospace design. The use of the methods required for a probabilistic framework across other aspects of aerospace fatigue

design and assessment/monitoring increases the useful return from the resources required to develop and implement a probabilistic framework. The interaction between the framework for implementing a probabilistic approach for safe-life components and the other aspects of aerospace design described in this section is visualised in Figure 3.

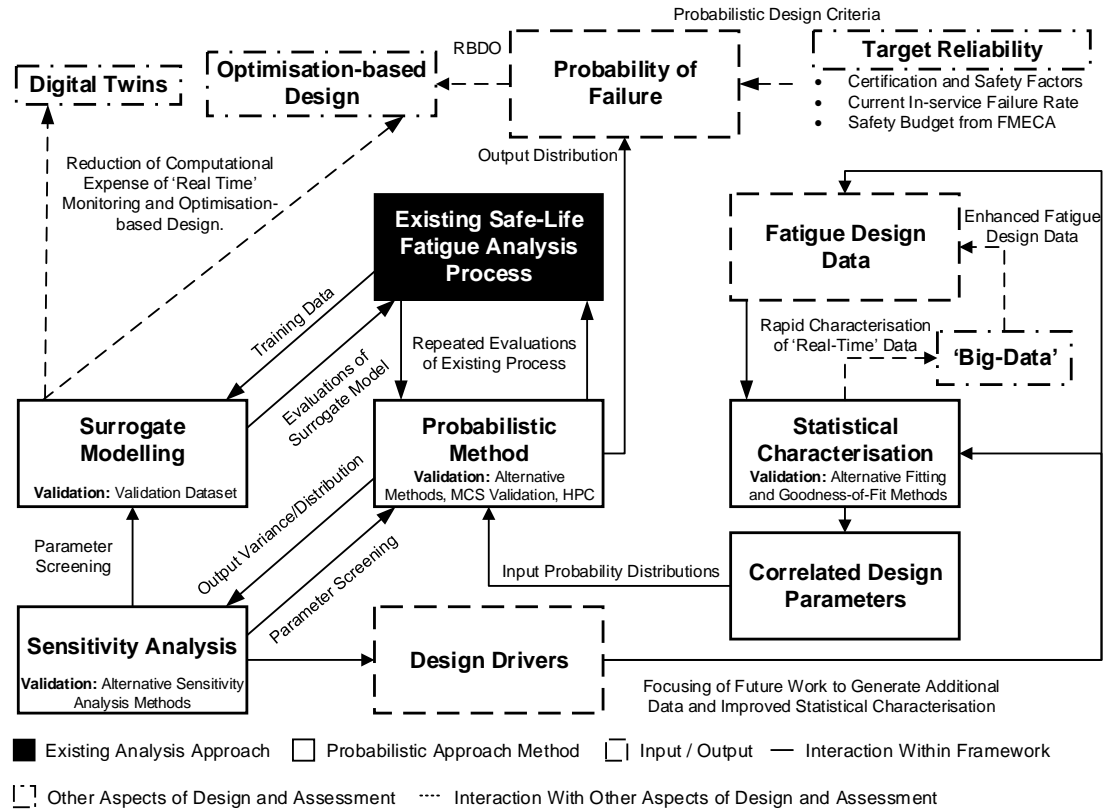


Figure 3: A demonstration of how the framework for implementing a probabilistic approach for the fatigue design of safe-life components interacts with other aspects and recent advancements in aerospace design.

CONCLUSION

This paper has presented a high-level framework to support the implementation of a probabilistic approach to the fatigue design of safe-life components. Probabilistic approaches provide an opportunity to better represent the variability present within fatigue design and analysis, enabling a challenge of the conservatism currently required within safe-life fatigue design. This paper has demonstrated the wide range of interactions that exist between the statistical characterisation, probabilistic, surrogate modelling and sensitivity analysis methods employed within the framework.

Significant challenges still exist which prevent the wider utilisation of a probabilistic framework for safe-life fatigue design. Most notably, the mindset change required to use target reliabilities as design criteria remains the major challenge when implementing a probabilistic framework, as challenges relating to computational expense and data availability can be mitigated through the use of surrogate modelling

and big-data approaches respectively. Each of these areas of challenge represent the future work of the authors.

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REFERENCES

- Booker, J. D., et al, (2001). *Designing Capable and Reliable Products*, Butterworth Heinemann.
- Braga D. F. O., et al, (2014). “Advanced design for lightweight structures: Review and prospects”, *Progress in Aerospace Sciences*, **69**, 29-39.
- Bury, K., (1999). *Statistical Distributions in Engineering*, Cambridge University Press.
- Buxbaum, O, (1981). “Landing Gear Loads of Civil Transport Airplanes”, *Aircraft Fatigue in the Eighties, Proceedings of the 11th Symposium of the International Committee on Aeronautical Fatigue*, Noordwijkerhout, Netherlands.
- Cortina, M., et al, (2012). “Sensitivity Analysis for General Aviation Risk Assessment”, *Proceedings of the 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference*, Honolulu, Hawaii.
- Cross, E., et al, (2012). “Prediction of Landing Gear Loads Using Machine Learning Techniques”, *Proceedings of the 6th European Workshop on Structural Health Monitoring*, Dresden, Germany.
- d’Ippolito, R., et al, (2007). “Robust and Reliable Fatigue Design of Automotive and Aerospace Structures”, *Proceedings of 6th International Conference on Durability and Fatigue (Fatigue 2007)*, Cambridge, UK.
- Dekker, S., et al, (2016). “Reliability modelling for rotorcraft component fatigue life prediction with assumed usage”, *The Aeronautical Journal*, **120** (1232), 1658-1692.
- EASA (European Aviation Safety Agency), (2016). *Certification Specifications and Acceptable Means of Compliance for Large Aeroplanes CS-25, Amendment 18*.
- Echard, B, et al, (2014). “A reliability analysis method for fatigue design”, *International Journal of Fatigue*, **59**, 292-300.
- Ferlin, M. et al, (2009). “DEFFI project for a new concept of fatigue design in the aerospace domain”, *Proceedings of the 50th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference*, California, USA,
- FlightRadar24, www.flightradar24.com [Accessed 12/12/2018].
- Forrester A., Keane, A. J., (2009). “Recent Advances in surrogate-based optimization”, *Progress in Aerospace Sciences*, **45** (1-3), 50-79.

- Genest, C., Favre, A.-C., (2007). "Everything You Always Wanted to Know about Copula Modeling but Were Afraid to Ask", *Journal of Hydrologic Engineering*, **12** (4), 347-368.
- Goh, Y. M., et al, (2009). "Improved utility and application of probabilistic methods for reliable mechanical design", *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, **223** (3), 199-214.
- Graham, K., et al, (2017). "Aircraft Fatigue Analysis in the Digital Age", *Proceedings of the 29th Symposium of the International Committee on Aeronautical Fatigue and Structural Integrity (ICAF2017)*, Nagoya, Japan.
- Habermann, G., (2007). "On the Selection of Test Factors For The Determination of Safe-Life", *Proceedings of the 24th Symposium of the International Committee on Aeronautical Fatigue and Structural Integrity (ICAF2007)*, Naples, Italy.
- Haugen, E. B., (1980). *Probabilistic Mechanical Design*, John Wiley & Sons.
- Holmes, G., et al, (2016). "Prediction of landing gear loads using machine learning techniques", *Structural Health Monitoring*, **15** (5), 568-582.
- Hoole, J., et al, (2016). "Safe-Life Fatigue and Sensitivity Analysis: A Pathway Towards Embracing Uncertainty?", *Proceedings of the Royal Aeronautical Society 5th Aircraft Structural Design Conference*, Manchester, UK.
- Hoole, J., et al, (2018). "Evaluating the Impact of Conservatism in Industrial Fatigue Analysis of Life-Limited Components", *12th International Fatigue Congress (Fatigue 2018)*, *MATEC Web of Conferences*, **165**.
- Long, M. W., Narciso, J. D., (1999). "Probabilistic Design Methodology for Composite Aircraft Structures", *Federal Aviation Administration Report DOT/FAA/AR-99/2*.
- Ocampo, J., et al, (2011). "Development of a Probabilistic Linear Damage Methodology for Small Aircraft", *Journal of Aircraft*, **48** (6), 2090-2016.
- Pianosi, F., et al, (2016). "Sensitivity analysis of environmental models: A systematic review with practical workflow", *Environmental Modelling & Software*, **79**, 214-232.
- SAE (Society of Automotive Engineers), (1997). *AIR5080: Integration of Probabilistic Methods into the Design Process*.
- Schijve, J., (2009). *Fatigue of Structures and Materials*, Springer.
- Schmidt, R. K., (2017). *Is Safe-Life Safe Enough?*, MSc Thesis, Cranfield University.
- Siddall, J. N., (1983). *Probabilistic Engineering Design: Principles and Applications*, Marcel Dekker Inc.
- Simpson, T., et al, (2001). "Metamodels for Computer-based Engineering Design: Survey and recommendations", *Engineering with Computers*, **17** (2), 129-150.
- Suresh, S., (1998). *Fatigue of Materials*, 2nd Edition, Cambridge University Press.
- van Ginneken, P., (2016). *Development of an Optimization Framework for Landing Gear Design*, MSc Thesis, Delft University of Technology.
- Zentuti, N. A., et al, (2017). "A review of probabilistic techniques: towards developing a probabilistic lifetime methodology in the creep regime", *Materials at High Temperatures*, 34:5-6, 333-341.
- Zhao, J., Adams, D. O., (2010). "Achieving Six-Nine's Reliability Using an Advanced Fatigue Reliability Assessment Model", *Proceedings of the American Helicopter Society 66th Annual Forum*, Phoenix, USA.